Proceedings of 2015 IEEE 12th International Conference on Networking, Sensing and Control
Howard Civil Service International House, Taipei, Taiwan, April 9-11, 2015

Self-organizing fuzzy sliding-mode control for a voice coil motor

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***Abstract*—Voice coil motor (VCM) is widely known as its top-quality of free friction, low noise, fast transient response and well repeatability. Yet the dynamic characteristic of a VCM is nonlinear and time-varying, thus the model-based conventional controller is difficult to achieve high-precision control performance for a VCM. To attack this problem, a self-organizing fuzzy sliding-mode control (SFSC) system is proposed in this paper. All of the fuzzy rules are online grown and pruned by the structure learning phase and the parameter learning phase is designed to tune the controller parameter in the gradient-descent-learning algorithm. From the experiment results, it shows that the proposed SFSC system can successfully control a VCM with favorable control response with enhanced disturbance rejection performance.**

Keywords—voice coil motor; fuzzy sliding-mode control; structure learning; parameter learning; microcontroller

I. Introduction

Voice coil motor (VCM) has excellent characteristic of its simple structure, low friction between motor and motor device and ability of high-frequency repeatability movement. The VCM is used in the applications of linear positioning control systems with small control range, such as an optical read/write head of a hard disk [1]. However, the dynamic equation of a VCM is difficult to obtain due to the nonlinear and time-varying motor behaviors. From the control design viewpoint, the conventional control technologies are always based on a good understanding of the control system dynamics, so it is very difficult to control a VCM by using conventional control theory.

In the past decade, several control methods have been studied for a VCM control [2-4]. In [2], the favorable position control performance can be achieved using the rule-based controller, but the fuzzy rules should be pre-constructed by time-consuming trial-and-error tuning procedure. In [3], an adaptive control is developed to track reference trajectories with small tracking error. However, the adaptive controller requires the structure of the system dynamic functions. In [4], a neural-network-based intelligent VCM control is proposed. Though the favorable control performance can be achieved, the intelligent VCM control design procedure requires heavy computation costs.

Since the fuzzy control (FC) system does not need a mathematical model, it has been proven to be a powerful tool [5]. Most of the operations in FC use the error and change-of-error as the fuzzy input variables. However, the huge amount of the fuzzy rules required makes the analysis complex. Some researchers proposed fuzzy sliding-mode control (FSMC) scheme [6, 7]. By defining the sliding surface as the input variable of fuzzy rules, the number of fuzzy rules can be reduced to a minimum number. But, the design of the fuzzy rules for FC and FSMC schemes has relied on a priori knowledge.

To resolve this problem, several learning methods have been proposed [8-10]. Though favorable control performance can be achieved in [8-10], the learning algorithms only take care of parameter learning but neglect structure learning of fuzzy rules. Time-consuming trial-and-error process is needed to determine the number of fuzzy rules. Generally, more fuzzy rules in FC and FSMC systems can achieve better control performance. To solve the problem of number determination in a fuzzy system, much interest has been focused on the structure learning approach for FC and FSMC [11-13]. The structuring learning in [11-13] often suffers from a heavy computation loading, thus they are not suitable for online practical applications.

Motivated by the previous discussions, a self-organizing fuzzy sliding-mode control (SFSC) system is proposed to possess high-accuracy position tracking performance of a VCM. The proposed SFSC system is designed to resolve the system uncertainties with both structure learning and parameter learning phases. In the structure learning phase, there are initially no fuzzy rules in the SFSC system. The structure learning phase is responsible for online fuzzy rule generation of the SFSC system. After structure learning, the parameter learning phase online tunes the controller parameters of the SFSC system by the gradient descent method to guarantee system stability. Finally, a microcontroller-based experimental setup for VCM position control is proposed. The experimental results show that the proposed SFSC system can automatically generate the fuzzy rules and tune the controller parameter, simultaneously, to achieve high-precision control performance.

978-1-4799-8069-7/15/$31.00

II. PROBLEM FORMULATION

By using Newton's second law, the mathematic equation of a VCM describes as [1]

$$F_t - F_f = (m+M)\ddot{x} + B\dot{x} \tag{1}$$

where x is the position of the table, M is the mass of the table, m is the mass of the payload, B is the viscous coefficient, F_t is the thrust force and F_f is the lumped friction force. The thrust force F_t is defined as

$$F_t = K_t i_a \tag{2}$$

where K_t is the thrust force coefficient and i_a is the coil current. The electric equation of a VCM can be given as [1]

$$v_a = R_a i_a + K_b \dot{x} + L_a \dot{i}_a \tag{3}$$

where R_a is the coil resistance, K_b is the back electromotive force coefficient, L_a is the coil inductance and v_a is the input voltage. The term L_a can be neglected in this study. From (1) and (3), the dynamics of the VCM can be represented as

$$\ddot{x} = f + gu + d \tag{4}$$

where $f = \dfrac{-(K_t K_b + R_a B)}{(m+M)R_a}\dot{x}$ is the system dynamic, $g = \dfrac{K_t}{(m+M)R_a}$ is the system control gain, $d = \dfrac{-F_f}{m+M}$ is the external disturbance, and $u = v_a$ is the control input. The control objective is to design the position x to track the position command x_c closely. Define a tracking error as

$$e = x_c - x \tag{5}$$

Substituting (4) into (5) yields

$$\ddot{e} = z - u \tag{6}$$

where the nonlinear term z is defined as $z = \ddot{x}_c - (1 - \dfrac{1}{g(x,\dot{x})})\ddot{x} - \dfrac{f(x,\dot{x}) + d}{g(x,\dot{x})}$. Assuming that all the parameters in the nonlinear term z are known, we can construct an ideal controller as [14]

$$u^* = k_1 \dot{e} + k_2 e + z \tag{7}$$

where k_1 and k_2 are positive constants. Imposing the control law $u = u^*$ upon (6), it follows that

$$\ddot{e} + k_1 \dot{e} + k_2 e = 0 \tag{8}$$

If k_1 and k_2 are chosen such that all roots lie strictly in the open left half of the complex plane, this implies that $\lim_{t\to\infty} e = 0$ for any initial condition [14]. However, the ideal controller (7) cannot be precisely obtained due to the nonlinear term z is unknown.

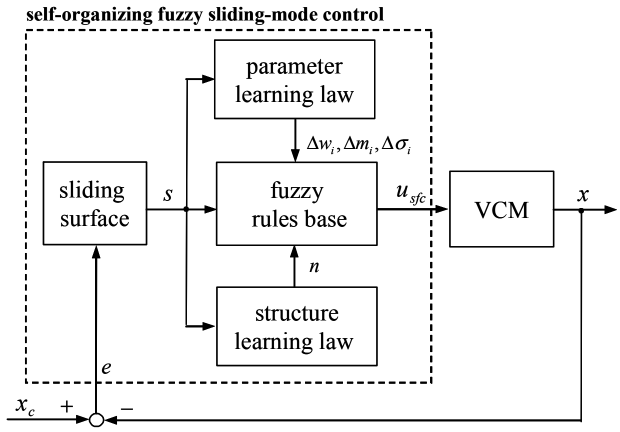

Fig. 1 The block diagram of the SFSC system for a VCM

III. DESIGN OF SFSC SYSTEM

In this paper, the SFSC system for a VCM is designed as shown in Fig. 1, where a sliding surface s is defined as

$$s = \dot{e} + k_1 e + k_2 \int_0^t e\, d\tau \tag{9}$$

Suppose that there are n fuzzy rules in the SFSC system as the following form

$$\text{Rule } i: \text{IF } s \text{ is } F_s^i, \text{THEN } u_{sfc} \text{ is } w_i \tag{10}$$

In order to reduce the computational loading of a microcontroller, triangular-typed functions and singletons are used to define the membership functions of IF-part and THEN-part, which are shown in Figs. 2(a) and 2(b), respectively. The rule firing strength of the i-th fuzzy rule ϕ_i can be given as

$$\phi_i = \begin{cases} 0 & ,\text{if } s < m_i + \sigma_i, s > m_i - \sigma \\ \dfrac{s - m_i + \sigma_i}{\sigma_i} & ,\text{if } m_i - \sigma_i \le s \le m_i \\ \dfrac{-s + m_i + \sigma_i}{\sigma_i} & ,\text{if } m_i \le s \le m_i + \sigma_i \end{cases} .$$

$$\text{for } i = 1,2,\ldots,n \tag{11}$$

where, in the *i*-th fuzzy rule, m_i is the center of the triangle function and σ_i is the length between the center to edge corners of the triangle. According the centre-of-gravity method to defuzzification, the controller output can be obtained as

$$u_{sfc} = \sum_{i=1}^{n} w_i \phi_i \tag{12}$$

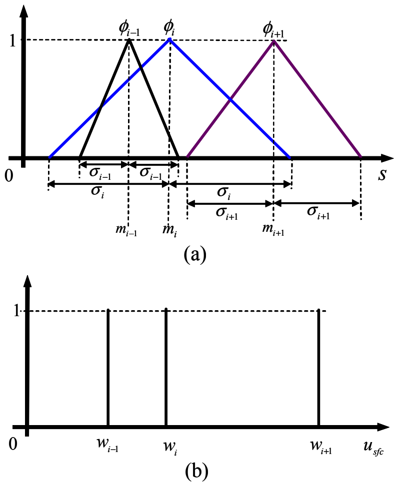

Fig. 2 Membership functions of IF part and THEN part

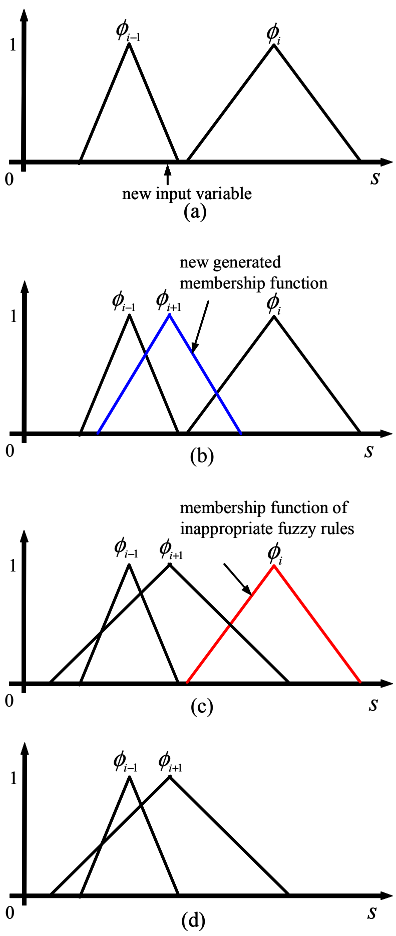

Fig. 3 Membership functions of IF part during structuring learning

A. Structure Learning Phase

The SFSC contains no fuzzy rules in the fuzzy rules base at the beginning, thus it will automatically generate the fuzzy rules. The objective of the structure learning phase is to ensure that at least one fuzzy rule is activated. Thus, the rule firing strength ϕ_i in (11) is used as the criterion to determine whether or not a fuzzy rule should be generated. As the fuzzy rules base cannot compute an appropriate output corresponds to present input variable, then a new fuzzy rule will be generated. Meanwhile, some of existing fuzzy rules will be removed if the fuzzy rules are inappropriate. For the first iteration, a fuzzy rule is generated with the initial parameters are given as

$$m_1 = s \tag{13}$$

$$\sigma_1 = \overline{\sigma} \tag{14}$$

$$w_1 = 0 \tag{15}$$

where $\overline{\sigma}$ is the width of the first fuzzy rule cluster. For subsequent iterations, find

$$K = \arg\max_{1 \le i \le n} \phi_i \tag{16}$$

where n is the number of fuzzy rules existing. K represented which fuzzy rule has the maximum rule firing strength. Once $\phi_K \le \phi_{th}$, where $\phi_{th} \in (0,1)$ a pre-given threshold, a new fuzzy rule must be generated. The initial associated parameters of the new fuzzy rule will be set as follows

$$m_{n+1} = s \tag{17}$$

$$\sigma_{n+1} = \beta \cdot \sum_{i=1}^{n} \sqrt{|s - m_i|} \tag{18}$$

$$w_{n+1} = 0 \tag{19}$$

where β decides the overlap degree. An input variable doest not fall within the membership function of the existing fuzzy rules as shown in Fig. 3(a), thus a new membership function for fuzzy rule is generated as shown in Fig. 3(b). A very large value of β generates a fuzzy set that covers a broad range of the input domain and most of fuzzy sets may be highly overlapped. On the contrary, a very small value of β generates a fuzzy set with almost no overlap with others fuzzy rules.

In order to make rule base number under control and also streamline the computational burden, a pruning algorithm is added for pruning the inappropriate fuzzy rules. By giving every fuzzy rule a density index, after during a given time Δt is possible to tell which rule base is inappropriate. Density index is define as

$$I_i(t) = \sum_{j=t-\Delta t}^{t} d_i(j), \text{ where } d_i(t) = \begin{cases} 0, if\ \phi_i = 0 \\ 1, if\ \phi_i > 0 \end{cases} \tag{20}$$

If the input variable falls between $m_i - \sigma_i \le s \le m_i + \sigma_i$ of the i-th fuzzy rule ($\phi_i > 0$), then the density of fuzzy rules will be given as one. After a given time, sum up the density index of each fuzzy rule during the time. The fuzzy rule which has the minimum density sum (I_i) signifies the least important. If $I_i \le I_{th}$ is satisfied as shown in Fig. 3(c), where I_{th} is the criterion of separating the important rules and the unimportant rules, then the i-th rule should be pruning as shown in Fig. 3(d).

B. Parameter Learning phase

Imposing the control law $u = u_{sfc}$ into (6) and using (7), yields

$$\ddot{e} + k_1\dot{e} + k_2 e = u^* - u_{sfc} = \dot{s} \tag{21}$$

Multiplying both sides of (21) by s gives

$$s\dot{s} = s(u^* - u_{sfc}) = s(u^* - \sum_{i=1}^{n} w_i\phi_i) \tag{22}$$

According to the gradient descent method, the parameter learning algorithm is derived to minimize the learning performance $s\dot{s}$ for achieving fast convergence of s. The parameter tuning law Δw_i for the t-th iteration is given by [15]

$$\Delta w_i(t) = -\eta_w \frac{\partial s\dot{s}}{\partial w_i(t)} = \eta_w s\phi_i \tag{23}$$

where η_w is a positive learning rate. The singleton control rule w_i is updated as

$$w_i(t+1) = w_i(t) + \Delta w_i(t) \tag{24}$$

By using chain rule, the parameter adaptive laws Δm_i and $\Delta\sigma_i$ for the i-th fuzzy rules can be obtained as

$$\Delta m_i(t) = -\eta_m \frac{\partial s\dot{s}}{\partial m_i(t)} = -\eta_m \frac{\partial s\dot{s}}{\partial u_{sfc}} \frac{\partial u_{sfc}}{\partial \phi_i} \frac{\partial \phi_i}{\partial m_i(t)}$$

$$= \begin{cases} -\eta_m \dfrac{w_i}{\sigma_i} s, \text{ if } m_i - \sigma_i \le s \le m_i \\ \eta_m \dfrac{w_i}{\sigma_i} s, \text{ if } m_i \le s \le m_i + \sigma_i \\ 0, \text{ otherwise} \end{cases} \tag{25}$$

$$\Delta\sigma_i(t) = -\eta_\sigma \frac{\partial s\dot{s}}{\partial \sigma_i(t)} = -\eta_\sigma \frac{\partial s\dot{s}}{\partial u_{sfc}} \frac{\partial u_{sfc}}{\partial \phi_i} \frac{\partial \phi_i}{\partial \sigma_i}$$

$$= \begin{cases} -\eta_\sigma w_i \dfrac{s - m_i}{\sigma_i^2} s, \text{ if } m_i - \sigma_i \le s \le m_i + \sigma_i \\ 0, \text{ otherwise} \end{cases} \tag{26}$$

where η_m and η_σ are positive learning rates. The parameters m_i and σ_i can be updated as

$$m_i(t+1) = m_i(t) + \Delta m_i(t) \tag{27}$$

$$\sigma_i(t+1) = \sigma_i(t) + \Delta\sigma_i(t) \tag{28}$$

Therefore, the SFSC system can automatically self-organizing the fuzzy rules and tune the rule parameters to approximate an ideal controller.

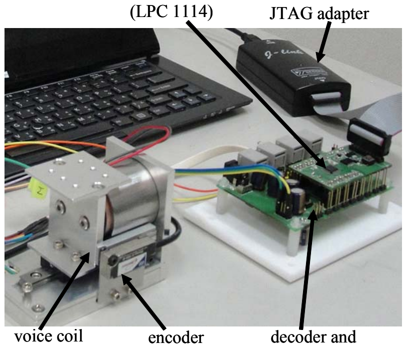

Fig. 4 Microcontroller-based experimental setup

IV. EXPERIMENTAL RESULT

In this paper, a hardware structure based on a microcontroller is proposed as shown in Fig. 4. The used 32-bit microcontroller (LPC1114FBD48) runs at 50MHz with 32KB of Flash and 8KB of SRAM based on the ARM® Cortex™-M0 processor. On the software side, we use Keil uVision IDE to write program and upload it to the control board. Two conditions are tested here. One is the nominal condition and the other is the payload condition by adding a payload on the table. To investigate the effectiveness of the proposed control system, a comparison between the FSMC [2] system and the proposed SFSC system is made.

First, the FSMC system is applied to the VCM. The fuzzy rules are given in the following form

$$\text{Rule i: IF } s \text{ is } F_s^i \text{, THEN } u_{fc} \text{ is } F_u^i \tag{29}$$

where in the i-th rule, F_s^i and F_u^i are the fuzzy sets of s and u_{fc}, respectively. The experimental results of the FSMC system with using 3 fuzzy rules are shown in Fig. 5. The tracking responses x are shown in Figs. 5(a) and 5(c), and the control inputs u_{fc} are shown in Figs. 5(b) and 5(d) for the nominal condition and payload condition, respectively. Though the accurate position tracking control performance can be achieve for the nominal condition, the degenerated tracking performance is resulted under the occurrence of payload variations. Later, the experimental results of the FSMC system with using 11 fuzzy rules are shown in Fig. 6. The tracking responses x are shown in Figs. 6(a) and 6(c), and the control inputs u_{fc} are shown in Figs. 6(b) and 6(d) for the nominal condition and payload condition, respectively. The experimental results show that the favorable control performance can be achieved for both of nominal condition and payload condition. However, the computation burden makes it hard to implement.

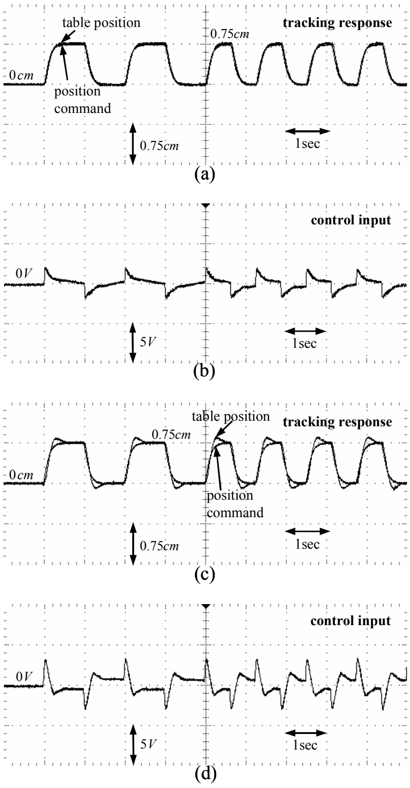

Fig. 5 Experimental results of the FSMC system with 3 fuzzy rules

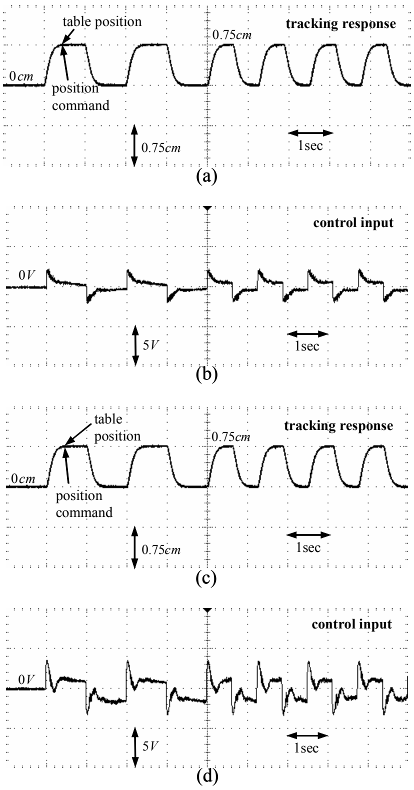

Fig. 6 Experimental results of the FSMC system with 11 fuzzy rules

To show the effectiveness of the proposed structure learning phase, the proposed SFSC system without pruning algorithm is applied to the VCM again. The controller parameters are selected as $k_1 = 1$, $k_2 = 0.25$, $\eta_w = 0.1$ and $\eta_m = \eta_\sigma = 0.01$, $\phi_{th} = 0.2$, $\bar{\sigma} = 1$ and $\beta = 0.8$. These values are chosen through some trials to achieve favorable control performance. The experimental results of the SFSC system without pruning algorithm are shown in Fig. 7. The tracking responses x are shown in Figs. 7(a) and 7(d), the control inputs u_{sfs} are shown in Figs. 7(b) and 7(e), and the numbers of the fuzzy rule are shown in Figs. 7(c) and 7(f) for the nominal condition and payload condition, respectively. The experimental results show that the SFSC system without pruning algorithm can achieve accurate tracking ability; however, the structure learning without pruning algorithm can not achieve optimal fuzzy rules structure.

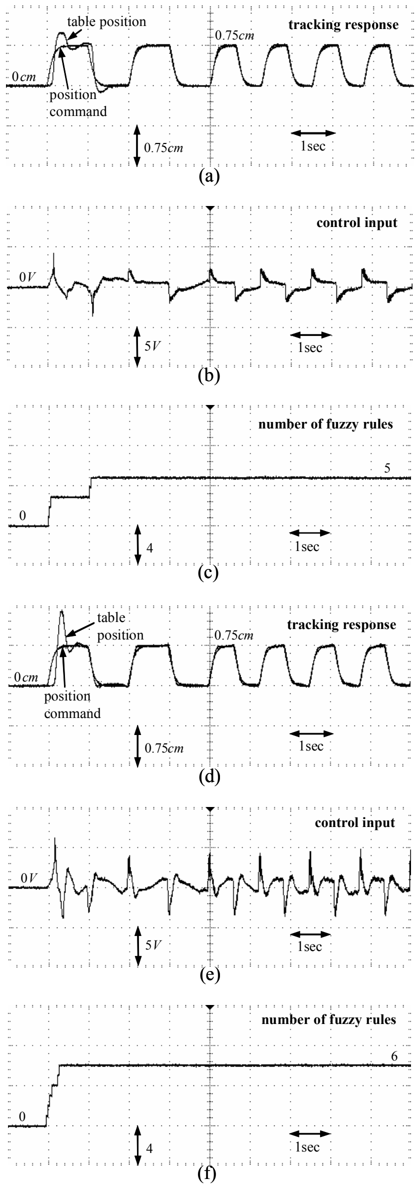

Fig. 7 Experimental results of the SFSC system without pruning algorithm

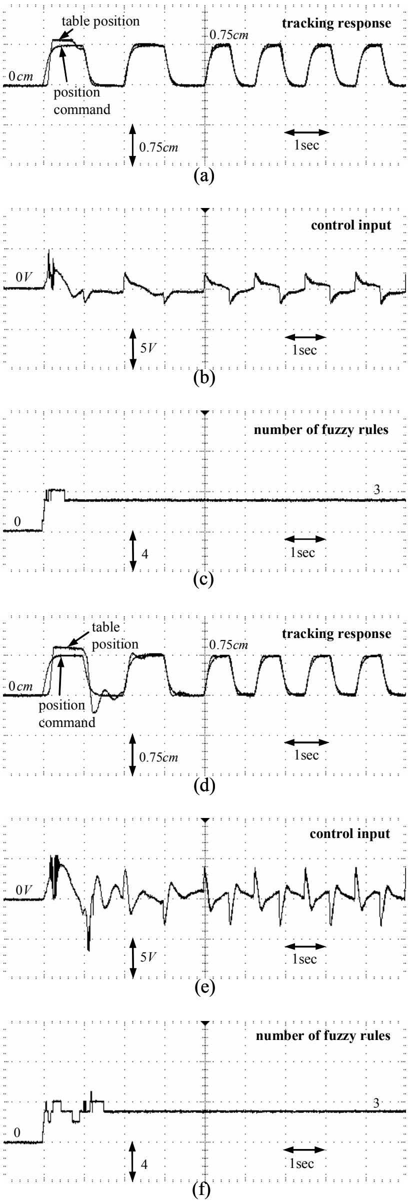

Fig. 8 Experimental results of the SFSC system with pruning algorithm

Finally, the proposed SFSC system with pruning algorithm is applied to the VCM again. The controller parameters are selected as $k_1 = 1$, $k_2 = 0.25$, $\eta_w = 0.1$ and $\eta_m = \eta_\sigma = 0.01$, $\phi_{th} = 0.2$, $I_{th} = 2$, $\bar{\sigma} = 1$ and $\beta = 0.8$. The experimental results of the SFSC system with pruning algorithm are shown in Fig. 8. The tracking responses x are shown in Figs. 8(a) and 8(d), the control inputs u_{sfs} are shown in Figs. 8(b) and 8(e), and the numbers of the fuzzy rule are shown in Figs. 8(c) and 8(f) for the nominal condition and payload condition, respectively. Through the illustrations, the excellent tracking responses can be given and the concise size of fuzzy rules base can be observed since the proposed structure learning scheme and the parameter learning laws are applied simultaneously. Meanwhile, the proposed rule generator which includes rules growing and rules pruning is effective and efficient without heavy computation costs.

V. CONCLUSIONS

The learning algorithm of the proposed SFSC system not only online generates and prunes the fuzzy rules but also online adjusts the parameters. The fuzzy rules of the SFSC system starts from zero and it can remove unimportant fuzzy rules to prevent the fuzzy rules to grow unboundedly. The ability of observe rules base can apparently reduce computation time and memory space. The parameter learning is designed to online approximate an ideal controller based on the gradient descent method. The experimental results show that the proposed SFSC system can achieve favorable control performance, such as high-precision linear motion, under the occurrence of payload variations.

ACKNOWLEDGMENT

The authors appreciate the partial financial support from the Ministry of Science and Technology of Republic of China under Grant MOST 103-2221-E-032-063-MY2.

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